# Electro-Optic Identification (EOID) Research Program

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## LONG-TERM GOALS

The goal of this research is to provide computer-assisted identification of underwater mines in electro-optic imagery. Identification algorithms will greatly reduce the time and risk to reacquire mine-like-objects for positive classification and identification.

## OBJECTIVES

The objectives are to collect electro-optic data under a wide range of operating and environmental conditions and develop precise algorithms that can provide accurate target recognition on this data for all possible conditions.

## APPROACH

The approach is to extend and verify the notional EOID architecture developed earlier. Algorithm efforts were focused on object detection using two approaches; object contrast, and convolution of well-know-objects in the Fourier domain. The approach for verification is to use the EOID data collection to configure and measure the effectiveness of object detection.

## WORK COMPLETED

The Northrop Grumman EOID architecture has been established as a baseline architecture for EOID processing of laser-line-scan (LLS) underwater imagery. The Northrop Grumman EOID automatic target recognition (ATR) architecture processes the underwater images in multiple steps using multiple processes. Images are first processed with image wide correction algorithms including modulus 4 line raster adjustment, $1/r^2$ horizontal brightness, and smoothing of spot interference. Next the image is scanned for regions of interest using two techniques; statistical blob contrast detection, and coarse object convolution detection in the Fourier frequency domain.

The EOID architecture and detection algorithms were verified using three sets of LLS data. The first set (PrelimNgLLS) was provided from tests on the Northrop Grumman LLS device in Spring 2001.

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| 14. ABSTRACT **The goal of this research is to provide computer-assisted identification of underwater mines in electro-optic imagery. Identification algorithms will greatly reduce the time and risk to reacquire mine-like-objects for positive classification and identification.** |
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This data set includes 57 files of 8bit TIF data 1280x1024. The PrelimNgLLS data set has 206 objects with good to excellent visibility. The other two data sets are from the EOID simultaneous data collection in August 2001 of the EOID test field at Costal Systems NSWC, Panama City Florida. The EOID collection includes imagery from the NG LLS device (EoidNgLLS) and Raytheon LLS device (EoidRayLLS). The data sets were converted from raw bit files to TIF files that covered an entire pass through the EOID object field. The EoidNgLLS set contained 96 large files of varying quality with a total of 1,708 objects. A data file is 1,280 pixels wide (with 210-pixel black band) and 6,500 to 123,000 pixels long. The EoidRayLLS set contains 121 large files of varying quality with a total of 1,701 objects. The EoidRayLLS files were 1024 pixels wide and lengths similar to the NG data set.

The verification data sets were manually ground truthed using information provided from the EOID data field. Files were displayed with manual enhancement of brightness, contrast, stretch histogram, and log transform to categorize objects and assign ratings. The images were assigned an object visibility rating (excellent, good, fair, poor) to investigate image quality on algorihtm performance. Generally, images were clear enough for objects to be detected. Data set object catagorization is summarized in  Table 1. The EoidRayLLS files had discontinuities in 32 of the 72 files with object imagery where image data was absent.

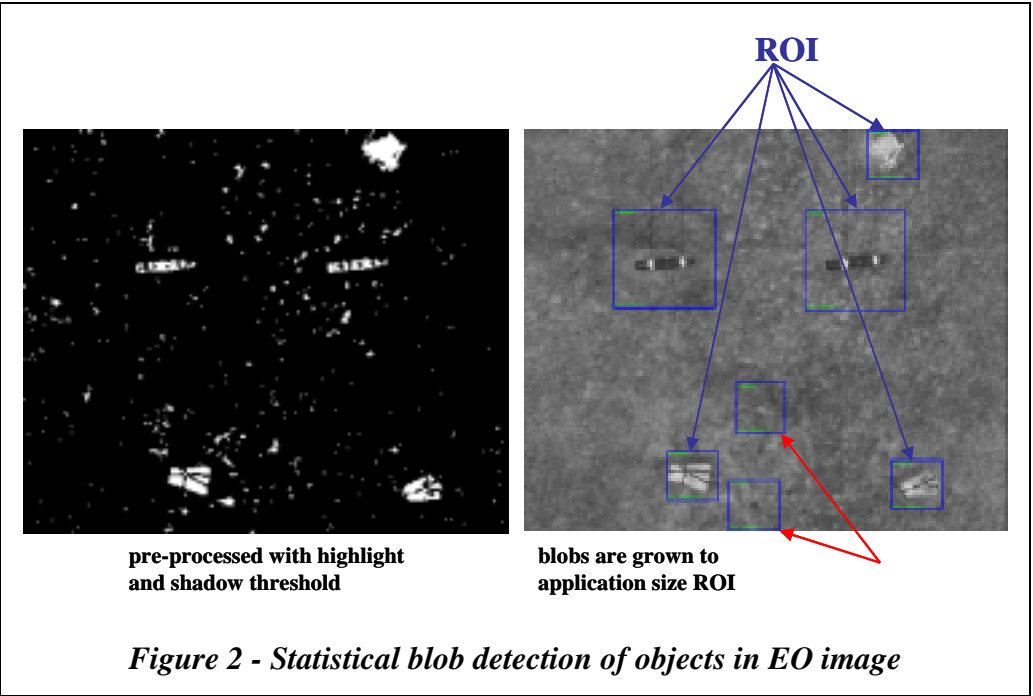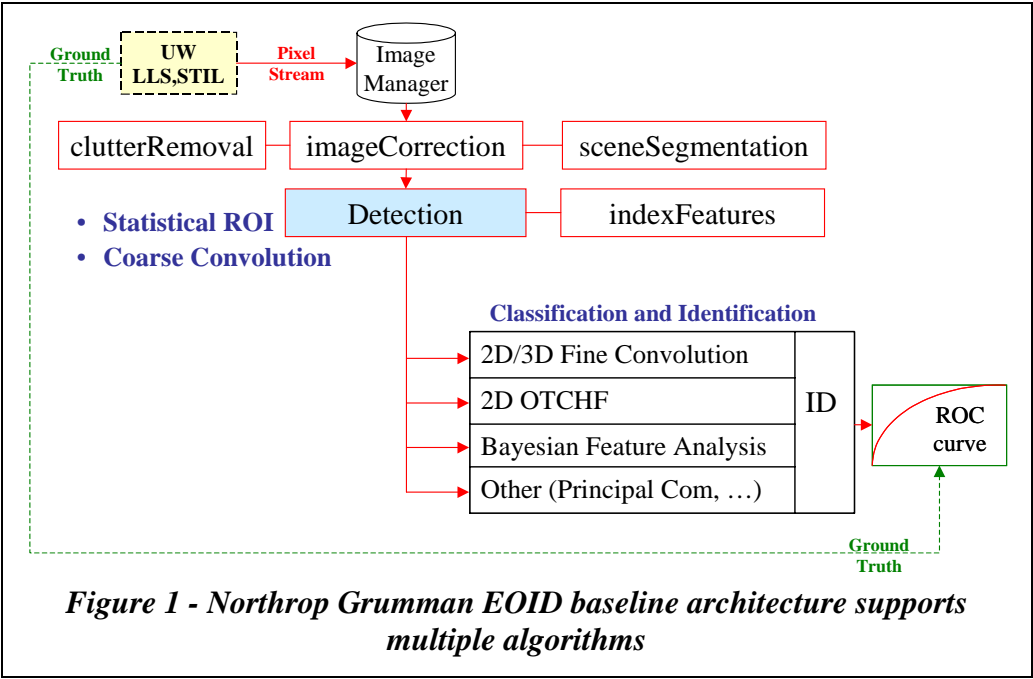*Table 1 - Objects were categorized in the EOID data sets*

| Dataset | Indistinct | Mines | Targets | Clutter | Total Objects |
|---------|-----------|-------|---------|---------|---------------|
| EoidNgLLS | 258 | 359 | 930 | 161 | 1708 |
| EoidRayLLS | 354 | 350 | 986 | 168 | 1858 |

Two types of systematic image distortion were observed and corrected; range brightness, and line rasterization. Systematic horizontal range brightness is expected to fall off as $1/r^2$ from the return laser reflection. However, we observed a more complex behavior in the EoidNgLLS data, with the brightest return not at the center. The EoidRayLLS data was more consistent, but also showed unexplained horizontal brightness behavior. The other systematic image distoration is a periodic difference in brightness from raster line to line modulus 4. This is presumed to be related to differences in the optical path of the four LLS mirrors. However, a simple modules 4 average did not completely remove the effect. The EoidRayLLS data drop-outs made the modules 4 correction more difficult since the modulus base had to be rediscovered at each drop-out (a convienent drop-out signature).

Two object detection algorithms were developed and verified, statistical blob detection based on a local contrast measure, and object convolution of mine shapes in the frequency domain. Both approaches have been used in previous ATR algorithms. The object contrast approach was used for its robustness to object shape, average brightness, and background effects. Convolution was used to leverage known information about the objects of interest. Disadvantages include unwanted clutter detection with contrast and dependance on sensor geometry with shape convolution.

**RESULTS**

The Northrop Grumman EOID ATR developmental architecture processes the underwater images in multiple steps using multiple processes. The architecture is illustrated in Figure 1 with information flow from top to bottom.



*Figure 1 - Northrop Grumman EOID baseline architecture supports multiple algorithms*



pre-processed with highlight and shadow threshold

blobs are grown to application size ROI

*Figure 2 - Statistical blob detection of objects in EO image*

EOID detections were analyzed against the algorithms, data source, object type, and image quality. An exhaustive analysis across these varibles was provided to ONR separately. Statistical contrast detection is illustrated in Figure 2 and results summarized in Table 2 and Table 3.

*Table 2- Northrop Grumman LLS data statistical blob contrast detection*

| Quality | Mines | Misc. | Targets | Total Detects |
|---------|-------|-------|---------|---------------|
| Excellent | 46/51 | 25/25 | 79/82 | 150/158  95% |
| Good | 54/65 | 25/29 | 154/154 | 233/248  94% |
| Fair | 50/141 | 44/62 | 275/297 | 369/500  74% |
| Poor | 13/102 | 16/45 | 261/397 | 290/544  53% |

*Table 3 - Raytheon LLS data statistical blob contrast detection*

| Quality | Mines | Misc. | Targets | Total Detects |
|---------|-------|-------|---------|---------------|
| Excellent | 50/59 | 34/34 | 133/133 | 217/226  96% |
| Good | 71/132 | 32/52 | 264/273 | 367/457  80% |
| Fair | 32/70 | 20/27 | 90/106 | 142/203  70% |
| Poor | 27/110 | 25/51 | 320/473 | 372/634  59% |

Overall detection was better with higher quality imagery. The two LLS detectors provided similar performance. Additional refinement of the contrast algorithms is expected to provide improved detection for low quality images.

The results for object convolution detection are summarized in Table 4 and Table 5..

*Table 4 - Northrop Grumman LLS data convolution detections from*
*4 Excellent, 5 Good, 3 Fair, and 0 Poor EOID images*

| | Detected | Total | Ratio |
|---|----------|-------|-------|
| Mines | 127 | 230 | 55% |
| Targets | 315 | 444 | 71% |
| Miscellaneous | 73 | 101 | 72% |
| Special | 14 | 37 | 38% |

*Table 5 - Raytheon LLS data convolution detections from*
*7 Excellent, 14 Good, 0 Fair, and 0 Poor EOID images*

| | Detected | Total | Ratio |
|---|----------|-------|-------|
| Mines | 100 | 135 | 74% |
| Targets | 210 | 293 | 72% |
| Miscellaneous | 56 | 72 | 78% |
| Special | 14 | 29 | 48% |

Analysis of missed convolution objects was traced to unexplained variations in the object pixel size. Convolution filters were adjusted to the instrument data altitude above the bottom and push-broom detector speed. Multiple passes over the same object yielded inconsistent model pixel sizes in the range and cross range direction. This is likely due to incorrect instrumentaion data or an unmodeled scaling parameter.

Convolution analysis on the PrelimNgLLS data set yielded perfect performance with 100% detection of all modeled objects. This result emphases the strength and vulnerabilities of convolution detection. That is, convolution provides excellent perfomance when all geometries are well known and well modeled.

Summary EOID detection performance is as follows.

- More statistical detections than convolution detections
- Expect statistical detector to provide even more robustness with additional work
- Convolution performance depends on accurate scaling
- Convolution may be more important for identification

**IMPACT/APPLICATIONS**

Baseline EOID object detection has been developed. Additional effort is expected to further improve the probability of detection and identification of underwater objects without fully relying on operator assistance.

**TRANSITIONS**

The detection results will be used as the first stage for laser-line-scan classification and identification algorithms developments in FY03. The resulting algorithms will be used to define and transition an automated underwater identification capability for the existing AN/AQS14A(V1) system which is currently in the fleet.  Currently the AN/AQS14A(V1) relies on operators for manual identification of the EOID images.

**RELATED PROJECTS**

The AN/AQS14A(V1) helicopter towed mine search system employs one of the laser-line-scan devices used in this EOID program to collect underwater imagery for mine detection and identification.  Currently four AN/AQS14A(V1) systems are deployed as fleet assets.

**PUBLICATIONS**

Snyder F.D., Dietz K. M., Esterrich T., Haley P. H., Cumm G., Esterrich T.; "Optical Detection of Underwater Objects", 2002 AUVSI Sea Day Conference, February 2002, Washington DC

Snyder F.D., Dietz K. M., Esterrich T., Haley P. H., Cumm G.; "Underwater Mine Detection and Identification with Laser Line Scan Sensor", 2002 NDIA Undersea Warfare Conference, March 2002, San Diego CA

Snyder F.D., Dietz K. M., Esterrich T., Haley P. H., Ethridge J; "Detection of Man-Made-Objects in Underwater Optical Images", 2002 NDIA Undersea Warfare Conference, March 2002, San Diego CA